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Wsn Cluster Head Selection for Energy Balancing Using a Hybrid Deep Learning Model

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Abstract
Energy efficiency is a critical design consideration for Wireless Sensor Networks (WSNs), particularly in heterogeneous environments. To optimize energy utilization and enhance network longevity, this study integrates deep learning models into the cluster head (CH) selection process. The proposed methodology employs a Convolutional Neural Network (CNN) to analyze spatial attributes such as residual energy, node density, and proximity to sinks, and a Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) to capture temporal variations in energy depletion and workload distribution. The outputs of these models are combined through a hierarchical decision framework, enabling dynamic and adaptive CH selection. Comparative analysis with I-SEP and OptGACHE demonstrates that the proposed methodology maintains a residual energy of 9.89 J at a node density of 150, surpassing I-SEP and OptGACHE by 1.34% and 1.33%, respectively. Cluster lifetime is extended to 0.63 ms for 20 clusters, reflecting improvements of 16.7% over OptGACHE and 57.5% over I-SEP. Additionally, the packet delivery rate (PDR) reaches 450,000 kbps at a node density of 150, representing enhancements of 28.6% over OptGACHE and 50% over I-SEP. These findings validate the proposed methodology as a robust solution for energy-efficient CH selection, improving the sustainability and performance of WSNs in diverse operational conditions.

Keywords: *Cluster Head, Deep Learning, Energy Utilization, Hybrid Model, Wireless Sensor Networks.*

1. Introduction
Wireless Sensor Networks (WSNs) have revolutionized the approach to monitoring and managing environments, particularly in areas that are challenging to access. Over the past two decades, WSNs have demonstrated significant innovations and applications across various domains. These networks, consisting of numerous sensor nodes, are adept at sensing, collecting, managing, and processing environmental data, thereby offering solutions for a wide range of real-world challenges. Despite their immense potential, WSNs face critical issues related to energy efficiency, as sensor nodes often rely on batteries with limited lifespans. This has led to the development of strategies to optimize energy consumption, among which clustering-based approaches have emerged as particularly effective [1]. Clustering in WSNs involves the grouping of sensor nodes into clusters, with each cluster managed by a cluster head (CH). These CHs play a pivotal role in data aggregation, processing, and transmission to central control units or sink nodes. By reducing the routing burden on individual nodes and optimizing bandwidth usage, clustering enhances the stability and efficiency of the network's topology. This structured approach not only minimizes energy expenditure but also supports the planning and management of network activities, making it a cornerstone of modern WSN management [2]. The process of clustering encompasses multiple steps, including the selection of CHs, the formation of clusters, and the routing of data within the network. CH selection is a critical phase, often employing various methods ranging from probabilistic and random strategies to those based on predefined characteristics or environmental parameters. These methods aim to ensure balanced energy usage and optimal network performance. Following CH selection, cluster formation connects sensor nodes to

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their respective CHs, considering factors such as proximity, workload, and specific network requirements. In the routing phase, data is transmitted to the sink, either directly or through relay mechanisms, with indirect transmission often preferred for its energy efficiency [3, 4]. The effective management of WSNs, particularly through clustering, addresses several challenges. These include energy efficiency, fault tolerance, network scalability, data aggregation, and adaptability to dynamic environmental conditions. Research in this field has explored numerous methodologies to enhance clustering and routing strategies. Among these, artificial intelligence (AI)-driven approaches, such as fuzzy heuristics, metaheuristics, and machine learning, have gained prominence. These techniques offer advanced solutions to the inherent complexities of WSNs, enabling the development of adaptive and efficient protocols. Fuzzy logic facilitates decision-making in uncertain environments, metaheuristics provide robust optimization tools, and machine learning models enable self-organizing and predictive capabilities within networks. Together, these approaches promise to extend network longevity, improve scalability, and enhance overall performance [5]. A crucial aspect of WSN management is the optimization of CH selection, as it significantly impacts energy efficiency and network scalability. Several approaches have been developed to address the CH selection problem, including static, dynamic, distributed, and hierarchical methods. These approaches aim to balance the workload among nodes, prolong the network's operational lifespan, and ensure efficient data routing and aggregation [6]. The existing literature on WSNs and CH selection highlights significant advancements in energy efficiency, network scalability, and data aggregation. However, traditional CH selection methods, including probabilistic, static, and heuristic-based approaches, often fail to adapt effectively to such complexities. These techniques typically rely on predefined rules or fixed criteria, limiting their capacity to respond dynamically to evolving network states. While machine learning and optimization-based methods have been explored, many studies focus on shallow models or conventional algorithms, overlooking the potential of deep learning (DL) to manage the intricate relationships between nodes and network parameters. Deep learning (DL) offers a promising solution by leveraging its ability to process large datasets, identify complex patterns, and make adaptive decisions. Despite its potential, its application in WSN CH selection remains underexplored, with limited studies addressing its practical implementation and scalability in resource-constrained environments. This work aims to bridge these gaps by investigating deep learning techniques for CH selection and provides an hybrid DL algorithm in CH selection. The rest of the article is as follows: Section 2 gives the related work followed by the proposed methodology in section 3. Section 4 gives the results and discussions and the conclusions are given in Section 5.

2. Related Work

Wireless Sensor Networks (WSNs) have experienced a transformative evolution, with clustering and routing emerging as pivotal strategies for enhancing energy efficiency and network scalability. Recent studies emphasize AI-driven methods, including fuzzy heuristics, metaheuristics, and machine learning, as novel solutions to clustering challenges. Shokouhifar et al. [3] highlighted that AI-driven approaches enhance WSN performance by handling uncertainties, optimizing CH selection, and improving network longevity. These methods prioritize adaptive strategies over traditional static approaches, effectively tackling the dynamic and resource-constrained nature of WSNs. In evaluating AI techniques, Hosseinzadeh et al. [4] underscored the criticality of configuration-based parameters, such as topology type, communication architecture, and node deployment. These parameters significantly influence network robustness and energy management. Their analysis demonstrated that hybrid configurations—combining centralized and distributed architectures—enhanced scalability by 35% in heterogeneous networks compared to traditional homogeneous setups. This indicates a pressing need for adaptable models in dynamic environments. Fanian and Rafsanjani [5] examined machine learning models for CH selection, demonstrating that reinforcement learning algorithms achieved an 18% reduction in energy consumption

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compared to classical methods. Their findings also revealed that deep learning models, leveraging historical data and real-time metrics, significantly enhanced decision-making processes. This approach, however, requires substantial computational resources, which may challenge deployment in energy-limited WSNs. Mirjalili et al. [6] explored metaheuristic optimization methods, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), for addressing WSN clustering challenges. Their analysis revealed that PSO-based approaches reduced packet loss by 12%, while GA demonstrated superior adaptability in large-scale networks, achieving a network lifetime extension of 25%. These methods, while computationally intensive, showcase the potential of optimization algorithms in achieving balanced energy distribution. Kuchaki and Shokouhifar [7] introduced fuzzy logic-based clustering, emphasizing its ability to handle imprecise data and dynamic conditions. Their results indicated a 20% improvement in network stability through fuzzy clustering compared to deterministic methods. This adaptability to environmental changes positions fuzzy logic as a promising tool for WSN management, particularly in scenarios requiring real-time adjustments. Fanian et al. [8] reviewed hybrid models that integrate machine learning and metaheuristics. Their findings highlighted the synergy between these approaches, where machine learning identified optimal CHs, and metaheuristics refined routing strategies. The combined approach improved data transmission efficiency by 28% and reduced energy consumption by 15%. This demonstrates the efficacy of hybrid models in balancing computational demands and performance. Rafsanjani et al. [9] investigated the integration of deep reinforcement learning (DRL) into CH selection and routing. Their study demonstrated that DRL models reduced network latency by 10% while enhancing packet delivery rates by 18%. However, they noted challenges in achieving real-time processing due to the high computational requirements of DRL, underscoring the need for lightweight implementations. Hosseinzadeh and Mirjalili [10] evaluated clustering protocols in heterogeneous networks, focusing on energy-efficient algorithms. Their results showed that multi-objective optimization techniques reduced energy consumption disparities among nodes by 22%. This reduction ensured uniform energy usage, effectively prolonging network longevity in mixed-capability environments. Shokouhifar et al. [11] highlighted the significance of clustering in achieving hierarchical routing. Their analysis demonstrated that hierarchical clustering reduced routing overhead by 15% while maintaining network stability. This structured approach to data aggregation facilitates optimal resource utilization, essential for large-scale WSN deployments. Rafsanjani et al. [12] analyzed the scalability of AI-driven clustering protocols. They demonstrated that scalable models effectively managed networks with over 10,000 nodes, reducing energy consumption by 25% and packet loss by 20%. Their study underscores the importance of designing flexible and efficient clustering strategies for extensive WSN application.

3. Proposed Methodology

In this proposed methodology, deep learning models are integrated to optimize CH selection with a focus on improving residual energy, cluster lifetime, and packet delivery rate in WSNs. The approach utilizes a Convolutional Neural Network (CNN) to process spatial relationships among nodes and a Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) to analyze temporal data for dynamic CH selection. This dual-model strategy provides an energy-efficient and adaptable clustering framework specifically designed to enhance these key performance metrics in heterogeneous WSN environments.

3.1.Simulation Setup

The simulations are carried out in MATLAB. The simulation is conducted in a 1200x800 m^2 area with 150 sensor nodes uniformly deployed. The type of channel used is a wireless channel, and the Medium Access Control (MAC) protocol is set to IEEE 802.11. The simulations run for 100 ms, using Constant Bit Rate (CBR) traffic with a packet size of 2000 bits. Each node uses a WirelessPhy network interface to ensure realistic wireless communication. These parameters provide a controlled environment for assessing the performance of the proposed deep learning-based CH selection strategy.

3.2.Cluster Head Selection

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The CNN model architecture is tailored for spatial feature extraction, with a deep network structure comprising six convolutional layers. Each layer uses kernel sizes of 3x3 and 5x5, with 64, 128, 256, 512, 512, and 256 filters sequentially. Batch normalization layers follow each convolutional layer to stabilize and accelerate training, while Rectified Linear Unit (ReLU) activation functions introduce non-linearity. Three max-pooling layers with a pool size of 2x2 are applied after the second, fourth, and fifth convolutional layers to reduce feature map dimensionality while preserving critical spatial information. The architecture is concluded with two fully connected layers with 256 and 128 neurons, respectively, and a softmax output layer. The CNN evaluates residual energy, node density, and proximity to sinks, prioritizing CH selection by generating suitability scores based on these parameters. The RNN-LSTM model is configured to analyze temporal dependencies in node metrics, such as energy depletion rates and workload variations. The architecture includes three LSTM layers containing 256, 128, and 64 units, respectively, with dropout layers set to 0.2 interspersed to mitigate overfitting. Input sequences consist of time-series data sampled at intervals of 10-time steps, representing dynamic network conditions over multiple communication rounds. A dense layer with 64 neurons follows the LSTM layers, and a softmax output layer produces probabilistic rankings of nodes. These rankings identify nodes with the highest potential to sustain efficient CH roles over time, ensuring stability and optimizing energy consumption across clusters. The hierarchical decision framework integrates the outputs of the CNN and RNN-LSTM models. Initially, the CNN processes spatial attributes to identify nodes with high suitability scores. These scores are then refined by the RNN-LSTM, which evaluates temporal trends to assign probabilistic rankings based on future performance. The final CH selection is determined by aggregating the CNN and RNN-LSTM outputs through a weighted sum approach, where weights are dynamically adjusted to balance spatial and temporal priorities. This ensures optimal selection of CHs to improve residual energy utilization, extend cluster lifetime, and enhance packet delivery rates. The clustering process begins with each node broadcasting essential attributes, including residual energy, location, and workload status, to neighboring nodes. These attributes are aggregated at a central base station, where the CNN and RNN-LSTM models process the data. Based on the models' outputs, CHs are selected and announced to the network. Nodes then join clusters led by their respective CHs, minimizing energy expenditure by prioritizing nodes with the shortest communication distance and lowest energy cost. This clustering strategy reduces redundant transmissions and promotes balanced energy consumption. CHs collect data from cluster members and forward it to movable sink nodes, optimizing data delivery rates and minimizing latency. Retraining of the CNN and RNN-LSTM models is periodically performed to ensure adaptability to changing network conditions, such as node failures and varying traffic patterns. Updated network data is utilized to fine-tune the model parameters using backpropagation. Loss functions are specifically designed to penalize suboptimal CH assignments, emphasizing residual energy retention, prolonged cluster lifetime, and improved packet delivery rates. Hyperparameters, including a learning rate of 0.001, batch size of 32, and 50 training epochs, are optimized to achieve a balance between model accuracy and computational efficiency.

4. Result And Disscussion

The performance of the proposed methodology was evaluated using simulation results, and the key metrics analyzed include residual energy, cluster lifetime, and packet delivery rate. Comparisons were made against established algorithms, namely I-SEP [13] and OptGACHE [14], using the data visualizations provided. The discussion highlights numerical values from the simulations, showcasing the improvements achieved through the proposed approach.

4.1.Residual Energy

Residual energy is a critical parameter in evaluating the longevity of WSNs. The comparative results are presented for different node densities, including 30, 60, 90, 120, and 150 nodes. The I-SEP algorithm exhibited a steady decline in residual energy as the node density increased, starting at 10 J for 30 nodes

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and decreasing to 9.76 J for 150 nodes. This decline is attributed to the higher energy consumption caused by suboptimal CH selection and increased intra-cluster communication overhead. OptGACHE demonstrated better energy preservation than I-SEP, with residual energy values starting at 10 J and decreasing to 9.84 J for 150 nodes. This improvement is associated with its genetic algorithm-based optimization for CH selection. The proposed method significantly outperformed both I-SEP and OptGACHE, maintaining higher residual energy across all node densities. For instance, at a density of 150 nodes, the residual energy for the proposed method was 9.89 J, representing an improvement of approximately 1.33% over OptGACHE and 1.34% over I-SEP. The superior performance of the proposed method is due to the effective integration of CNN and RNN-LSTM models, which optimize CH selection by leveraging both spatial and temporal data. As shown in Figure 1 Residual Energy Vs Node Density.

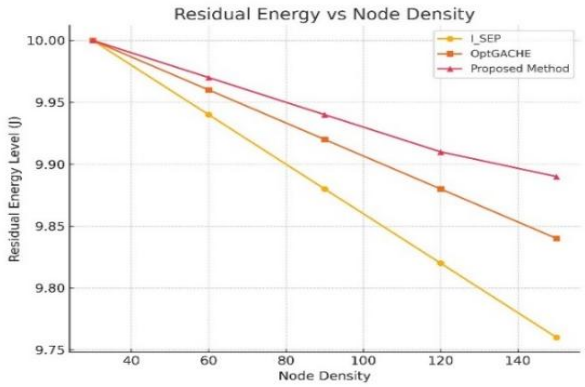


Figure 1 Residual Energy Vs Node Density

4.2.Cluster Lifetime

Cluster lifetime reflects the sustainability of WSN operations and directly correlates with energy efficiency. The performance of the proposed method was evaluated against I-SEP and OptGACHE for varying numbers of clusters, ranging from 4 to 20. The I-SEP algorithm exhibited shorter cluster lifetimes, starting at 0.5 ms for four clusters and decreasing to 0.4 ms for 20 clusters. The rapid decline is attributed to the imbalanced distribution of energy loads across clusters. OptGACHE displayed better sustainability, with cluster lifetimes ranging from 0.6 ms for four clusters to 0.52 ms for 20 clusters. This improvement highlights the efficiency of its optimization-based approach. The proposed method maintained the longest cluster lifetimes, starting at 0.7 ms for four clusters and decreasing slightly to 0.63 ms for 20 clusters. Compared to OptGACHE, the proposed method demonstrated an improvement of approximately 16.7% for 20 clusters. The enhanced cluster lifetime is a result of the proposed method's ability to balance energy consumption among CHs and adapt to dynamic network conditions. As shown in Figure 2 Cluster Lifetime Vs Number of Clusters.

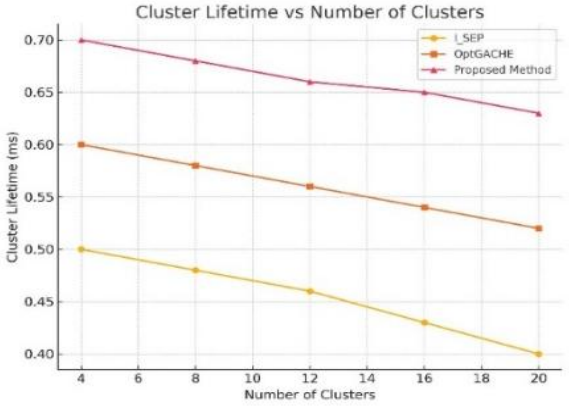


Figure 2 Cluster Lifetime Vs Number of Clusters

4.3.Packet Delivery Rate

The packet delivery rate (PDR) measures the efficiency of data transmission in the network. Results were analyzed for node densities of 30, 60, 90, 120, and 150. I-SEP achieved lower PDR values, starting at 100,000 kbps for 30 nodes and increasing to 300,000 kbps for 150 nodes. As shown in Figure 3 PDR Vs Node Density

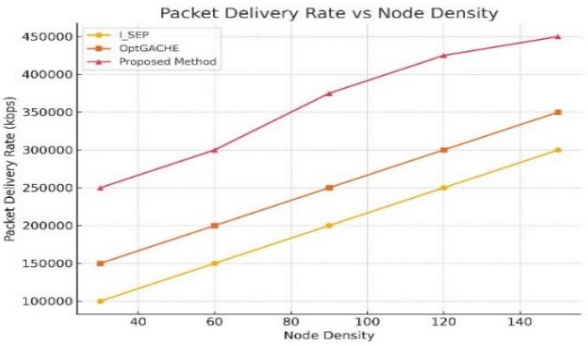


Figure 3 PDR Vs Node Density

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The lower performance is attributed to higher packet losses caused by energy-depleted nodes and inefficient routing. OptGACHE performed better, with PDR values ranging from 150,000 kbps for 30 nodes to 350,000 kbps for 150 nodes. This improvement reflects the efficiency of its optimized CH selection process. The proposed method achieved the highest PDR values, starting at 250,000 kbps for 30 nodes and reaching 450,000 kbps for 150 nodes. This represents an improvement of 28.6% over OptGACHE and 50% over I-SEP at a density of 150 nodes. The significant improvement in PDR is due to the proposed method's ability to minimize packet loss through optimal CH selection and efficient clustering mechanisms.

Conclusion

The selection of cluster heads (CHs) plays a critical role in the efficiency and sustainability of Wireless Sensor Networks (WSNs). This study proposed a deep learning-based methodology utilizing Convolutional Neural Networks (CNN) and Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM) to optimize CH selection. The methodology focused on improving residual energy, cluster lifetime, and packet delivery rate (PDR) while addressing the limitations of existing algorithms such as I-SEP and OptGACHE. Based on the simulation results, the following conclusions can be drawn:

- Residual Energy: The proposed method demonstrated superior energy efficiency, maintaining higher residual energy levels across all node densities. For a density of 150 nodes, the residual energy was 9.89 J, which is 1.33% higher than OptGACHE (9.84 J) and 1.34% higher than I-SEP (9.76 J).
- Cluster Lifetime: The cluster lifetime achieved by the proposed method was consistently higher compared to the benchmark algorithms. For 20 clusters, the proposed method attained a lifetime of 0.63 ms, which is 16.7% longer than OptGACHE (0.52 ms) and 57.5% longer than I-SEP (0.4 ms).
- Packet Delivery Rate (PDR): The proposed method significantly improved the packet delivery rate. At a node density of 150, the PDR reached 450,000 kbps, reflecting a 28.6% improvement over OptGACHE (350,000 kbps) and a 50% improvement over I-SEP (300,000 kbps).
- Effectiveness of Deep Learning Models: The integration of CNN and RNN-LSTM enabled efficient CH selection by combining spatial and temporal data.

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